



Hybrid unscented particle filter based state-of-charge determination for lead-acid batteries



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ABSTRACT

Accurate prediction of cell SOC (state of charge) is important for the safety and functional capabilities of the battery energy storage application system. This paper presents a hybrid UPF (unscented particle filter) based SOC determination combined model for batteries. To simulate the entire dynamic electrical characteristics of batteries, a novel combined state space model, which takes current as a control input and let SOC and two constructed parameters as state variables, is advanced to represent cell behavior. Besides that, an improved UPF method is used to evaluate cell SOC. Taking lead-acid batteries for example, we apply the established model for test. Results show that the evolved combined state space cell model simulates battery dynamics robustly with high accuracy and the prediction value based on the improved UPF method converges to the real SOC very quickly within the error of $\pm 2\%$.

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1. Introduction

As being robust, tolerant to abuse and having high surge-to-weight ratio with low cost, lead-acid batteries are widely used in numerous fields, which range from the relatively small portable equipments to the extremely large systems in loading level, such as telecommunication facilities, motor vehicles, emergency lighting alarm and power generations plants, etc. Real-time estimation of cell SOC, i.e., available capacity, is vital to the safety and functional capabilities of the overall system. Failure of a battery might lead to reduced performance, operational damage and even disastrous result.

Different estimation methods have been evaluated in many literatures. Some of them are related with voltage measurement, like fixed cut-off voltage when discharging, open circuit voltage, voltage under load, etc. Besides that, chemistry-dependent methods, impedance analysis [1,2], electrochemical modeling [3], and circuit models [2,4,5] are also common selection. These methods depend on the special concrete models and are hard to extract model parameters. ANN (artificial neural network) based methods [6–9] are widely utilized for capacity evaluation, which don't require knowledge of cell internal structure but rely greatly on the net training data, so do Fuzzy-logic-based models [9,10]. Techniques using EKF (extended kalman filter) [11–13] linearize the cell model equations and implement a Kalman filter to update the SOC. The

linearization to formulate the EKF results in the low convergence rate and reduces the prediction accuracy. UKF techniques [14] approximate nonlinear cell model with Gaussian probability distribution, which behave better but still converge a little slow. Particle filters adopt Monte Carlo sampling methods which are able to represent any probability density function, and approach the Bayesian optimal estimate with sufficient samples. Well designed particle filter methods can be made more accurate than the EKF and UKF ones. [15–19] presents a particle filter based method for SOC determination. To accurately estimate the SOC of a battery with the UPF (unscented particle filter) method, a very precise battery state-space model must be available [15]. adopts an electrochemical model for cell, which is usually difficult to build an accurate one because of the complexity of the electrochemical reaction process [16]. constructs a combined exponential equation to represent the relation among cell capacity, internal impedance, aging rate and cycle number [17]. employs SOC as the only state variable to describe the dynamics of the cell [18]. takes into account the hysteresis effect of charging/discharging current to cell performance besides SOC [19]. takes the drift current as the state variable besides cell SOC and employs more parameters like running mileage into model states. Besides the current, temperature, cycle number, storage time, available and nominal capacity, cell, a dynamic nonlinear system, behaves differently under the influence of nonlinear open-circuit voltage, transient response, hysteresis effect and so on. Moreover, those data like running mileage or life cycle can't be accessed directly at most time. So a more comprehensive

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and workable model, considering the entire dynamic electrical characteristics, is required to be established to simulate cell behavior. When employing UPF method to solve the cell state-space model, traditional methods [16–19] usually start to predict cell SOC with some random initial particles, which results in more time or greater number of particles to access the real value. So an improved UPF method is required to shorten the convergence time with fewer particles when evaluating available capacity.

This paper advances a hybrid UPF (unscented particle filter) based model to describe cell dynamics and estimate its SOC with high confidence. It is organized as follows. Firstly, we discuss a simple discrete state space cell model, which uses SOC as the only state variable and current as a control input. Secondly, an equivalent electrical battery model is introduced to simulate cell dynamics. Thirdly, a combined state space model is established to evaluate battery behavior, such as available capacity, open-circuit voltage, hysteresis effect and transient response, etc. Finally, we apply an improved UPF based method for SOC prediction of lead-acid batteries at different discharging and charging current. Results of lab tests on LEOCH DJ300 (2V/300Ah) lead-acid batteries with pulse discharging current, compared with model prediction of different methods, are presented.

2. Discrete state space cell model with one state and one input

Cells, nonlinear dynamic systems, can be represented by a discrete state-space form. Using cell remaining capacity $SOC(k)$ as the only system state and instantaneous current $i^\pm(k)$ as an input, we may describe system dynamics with the following state space model [6,11],

$$SOC(k) = SOC(k-1) - \frac{\eta(i^\pm(k), T(k)) \Delta t}{C_{Capacity}} i^\pm(k), \quad k = 1, 2, \dots \quad (1)$$

$$V(k) = [K_0, K_1, K_2, K_3, K_4] [1, SOC(k), 1/SOC(k), \ln(SOC(k)), \ln(1 - SOC(k)))]^T - i^\pm(k) R^\pm \quad (2)$$

where $\eta(i^\pm(k), T(k))$ is cell coulombic efficiency which differs with charging/discharging current $i^\pm(k)$ and cell temperature $T(k)$ at the k th sample time. Δt is the sampling period and $C_{Capacity}$ is the nominal capacity of cell. The vector $V(k)$ is the cell terminal voltage, $K_i (i = 1, 2, 3, 4)$ is the constant chosen to make the model fit the data well, and $R^\pm$ is the cell internal resistance which differs for different charge/discharge state and SOC level. It acts as a positive resistance R^- when discharging with current i^- and a negative resistance R^+ when charging with current i^+ .

Assume that open circuit voltage.

$$V_{oc}(SOC(k)) = [K_0, K_1, K_2, K_3, K_4] [1, SOC(k), 1/SOC(k), \ln(SOC(k)), \ln(1 - SOC(k)))]^T \quad (3)$$

Cell output Equation (3), turned to be a linear model, can be written as.

$$V(k) = V_{oc}(SOC(k)) - i^\pm(k) R^\pm \quad (4)$$

Drawn as an equivalent circuit, this output equation is depicted in Fig. 1. Then we may find that the output function, which just makes a limited constant $R^\pm$ represent the cell internal resistance, doesn't reflect the cell internal resistance enough. It doesn't characterize the transient response and hysteresis effect of cell which will contribute to the difference between the predicted cell voltage and the real one.

3. An equivalent electrical battery model

As shown in Fig. 2 [5], advances an electrical model to describe the dynamic characteristics of a battery. Self-discharge resistor ($R_{self_Discharge}$) characterizes the self-discharge energy loss. Full-capacity capacitor C (Capacity) represents the available capacity stored in the battery. A current-controlled current source is used to model the cell behavior among SOC, runtime and initial capacity. On the other hand, a voltage-controlled voltage source is employed to bridge SOC to open-circuit voltage. The shaded RC parallel network, consisting of $R_{transient_S}$, $C_{transient_S}$, $R_{transient_L}$ and $C_{transient_L}$, is used to characterize the hysteresis effect and transient response of cell.

The electrical battery model captures almost the entire dynamic electrical characteristics: nonlinear open-circuit voltage, current, temperature, cycle number, storage time, transient response, hysteresis effect, available and nominal capacity, etc.

Describing the electrical battery model with state space functions, we may get the state function.

$$\begin{bmatrix} V_{soc}^g \\ V_2 \\ V_2 \end{bmatrix} = \begin{bmatrix} 0, 0, 0 \\ 0, \frac{-1}{R_{transient_S} C_{transient_S}}, 0 \\ 0, 0, \frac{-1}{R_{transient_L} C_{transient_L}} \end{bmatrix} \begin{bmatrix} V_{soc} \\ V_1 \\ V_2 \end{bmatrix} + \begin{bmatrix} -1 \\ \frac{1}{C_{Capacity}}; \frac{1}{C_{transient_s}}; \frac{1}{C_{transient_L}} \end{bmatrix} i \quad (5)$$

and the output function

$$V = [1, -1, -1] [V_{soc}, V_1, V_2]^T - i R_{series} \quad (6)$$

Discretized at a small sampling period Δt and combined with SOC description (1), the equations can be written as follows.

$$\begin{bmatrix} SOC(k) \\ V_{soc}(k) \\ V_1(k) \\ V_2(k) \end{bmatrix} = \begin{bmatrix} 1, 0, 0, 0 \\ 0, 1, 0, 0 \\ 0, 0, 1 - \frac{\Delta t}{R_{transient_S} C_{transient_S}}, 0 \\ 0, 0, 0, 1 - \frac{\Delta t}{R_{transient_L} C_{transient_L}} \end{bmatrix} \begin{bmatrix} SOC(k-1) \\ V_{soc}(k-1) \\ V_1(k-1) \\ V_2(k-1) \end{bmatrix} + \begin{bmatrix} -1 \\ \frac{-\eta(i^\pm(k), T(k))}{C_{Capacity}}; \frac{1}{C_{transient_S}}; \frac{1}{C_{transient_L}} \end{bmatrix} \Delta t i^\pm(k)$$

$$V(k) = [0, 1, -1, -1] [SOC(k), V_{soc}(k), V_1(k), V_2(k)]^T - i^\pm(k) R_{series} \quad (7)$$

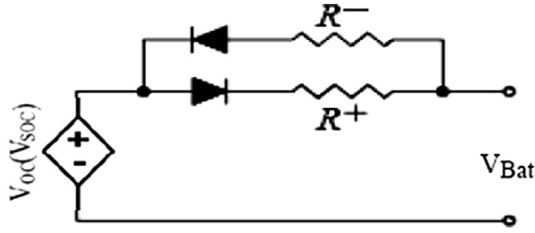


Fig. 1. Equivalent circuit from one state model.

An accurate SOC estimation of this model depends on three aspects: the initial SOC, calculation of SOC consumption and that of open circuit voltage V_{oc} . However, it's short of equations to describe the relations between open circuit voltage V_{soc} and cell SOC, which may lead to high prediction error and can't converge to the real available capacity as time goes on.

4. Combined state space model evolved from equivalent electrical battery model

Since the state space of one state model characterizes the correlation of the two greatly, we employ (3) to represent cell open circuit voltage $V_{oc}(SOC)$, i.e., V_{soc} .

At the same time, comparing the state equation of one state model and that of state $V_{oc}(SOC)$ in (5), we may discover that they have the same discipline in case that the coulomb efficiency $\eta(i^\pm(k), T(k))$ is 1. On the other hand, it means the description of state $V_{oc}(SOC)$ doesn't consider the problem of coulomb efficiency, which changes with temperature and charging/discharging rate. So syncretizing the equivalent electrical battery model and one state model together, we achieve a combined state space model.

$$\begin{bmatrix} \dot{SOC} \\ \dot{V}_1 \\ \dot{V}_2 \end{bmatrix} = \begin{bmatrix} 0, 0, 0 \\ 0, \frac{-1}{R_{Transient_S} C_{Transient_S}}, 0 \\ 0, 0, \frac{-1}{R_{Transient_L} C_{Transient_L}} \end{bmatrix} \begin{bmatrix} SOC \\ V_1 \\ V_2 \end{bmatrix} + \begin{bmatrix} \frac{-\eta(i^\pm, T)}{C_{Capacity}} \\ \frac{1}{C_{Transient_S}} \\ \frac{1}{C_{Transient_L}} \end{bmatrix} i \quad (8)$$

$$V = [1, -1, -1] [V_{oc}(SOC), V_1, V_2]^T - i R_{series}^\pm$$

Using a small sampling period Δt , a discrete time approximate model may then be written as.

$$\begin{bmatrix} SOC(k) \\ V_1(k) \\ V_2(k) \end{bmatrix} = \begin{bmatrix} 1, 0, 0 \\ 0, 1 - \frac{\Delta t}{R_{Transient_S} C_{Transient_S}}, 0 \\ 0, 0, 1 - \frac{\Delta t}{R_{Transient_L} C_{Transient_L}} \end{bmatrix} \begin{bmatrix} SOC(k-1) \\ V_1(k-1) \\ V_2(k-1) \end{bmatrix} + \begin{bmatrix} \frac{-\eta(i^\pm(k), T(k))}{C_{Capacity}}; \frac{1}{C_{Transient_S}}; \frac{1}{C_{Transient_L}} \end{bmatrix} \Delta t i^\pm(k) \quad (9)$$

$$V(k) = V_{oc}(SOC(k)) - [0, -1, -1] [SOC(k); V_1(k); V_2(k)] - i^\pm(k) R_{series}^\pm$$

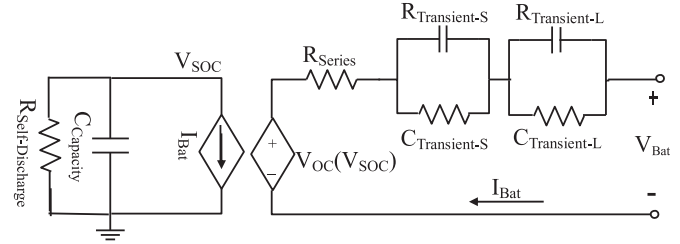


Fig. 2. Electrical battery model used to capture the entire dynamic characteristic.

Let

$$x = [SOC, V_1, V_2]^T, D = -R_{series}^\pm, y = V$$

$$A = \begin{bmatrix} 1, 0, 0; \\ 0, 1 - \frac{\Delta t}{R_{Transient_S} C_{Transient_S}}, 0; \\ 0, 0, 1 - \frac{\Delta t}{R_{Transient_L} C_{Transient_L}} \end{bmatrix}, B = \begin{bmatrix} \frac{-\eta(i^\pm(k), T(k))}{C_{Capacity}}; \\ \frac{1}{C_{Transient_S}}; \\ \frac{1}{C_{Transient_L}} \end{bmatrix} \Delta t,$$

$$g(x) = V_{oc}(SOC(k)) - [0, -1, -1] [SOC(k); V_1(k); V_2(k)]$$

(9) can be transformed as

$$\begin{aligned} x(k) &= Ax(k-1) + Bi^\pm(k), \\ y(k) &= g(x(k)) + Di^\pm(k), k = 1, 2, \dots, N \end{aligned} \quad (10)$$

where N is the sample times.

Contrast to the model in Refs. [11], this model has the same advantages of reflecting the effect of SOC and internal resistance and the hysteresis effect resulted from RC network. Moreover, it's more easy for understand and realization, and gives an insight into the cell internal mechanism.

5. Hybrid UPF based SOC determination model

The evolved combined state space model for cell can be linear in state equations, but is nonlinear in the output formula. Traditional solve methods include Extended Kalman Filter (EKF), UKF (unscented kalman filter), etc. Compared to the EKF [11–13], the UKF [14] does not require to explicitly calculate the Jacobian or Hessian matrix.

Particle filter can model arbitrary distributions and is often a more accurate alternative for the EKF or UKF with the advantage that they may approach the Bayesian optimal estimate with

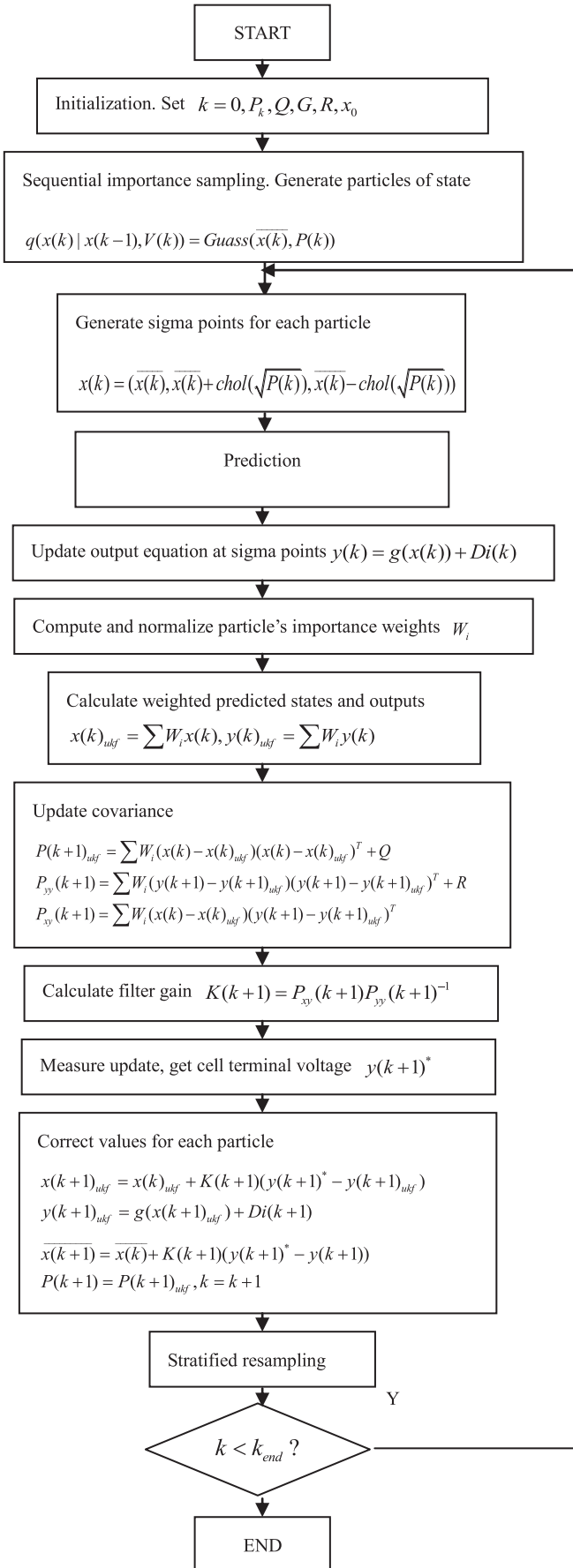


Fig. 3. The execution diagram of UPF method.

sufficient samples. The conventional one, treated for easy implementation, simply ignores $V(k)$. Comparatively, UKF can easily merge the most recent observation into the state estimation. To avoid their limitations and take advantage of the good features of both UKF and particle filters, we adopt UKF to generate the proposal distribution for the particle filter. Assume that each particle was satisfied with Gauss distribution, which is satisfied with.

$$q(x(k) | x(k-1), y(k)) = \text{Guass}(\bar{x}(k), P(k)), i = 1, 2, 3 \quad (11)$$

where $\bar{x}(k)$ and $P(k)$ are the mean and covariance of state variable $x(k)$ at the k th sample time.

Then the synthetic UPF determination model is established as follows.

$$\begin{aligned} x(k) &= Ax(k-1) + Bi^\pm(k) + Gw(k), w(k) \sim N(0, Q) \\ y(k) &= g(x(k)) + Di^\pm(k) + v(k), v \sim N(0, R), k = 1, 2, \dots, \end{aligned} \quad (12)$$

where G is the standard deviation of process noise, Q and R is the covariance of process and measurement noise.

The overall model development scheme can be organized by four steps [15]. First is sensor data, where some target parameters are measured, such as I (current), T (temperature) and V (terminal voltage), etc. The second is data preprocessing, which includes cleaning, normalization, transformation, feature extraction and selection, etc, and then training and test set is acquired. The third step is regression model identification. The values of coefficient matrix in (11) are access with least square regression algorithm based on the training set. Accommodating the sources of uncertainty in feature extraction, regression modeling and measurement, the noise samples w and v are picked from zero mean Gaussian distributions whose standard deviations G and covariance (P , Q , R) are derived from the given training data.

The last step is model evaluation. When start prediction with Kalman filter, it is assumed that the initial value of the state has a known mean value and variance. If no such data is available, the estimate will have a transient in the initial phase of the filtering. If cells are in good states and have enough capacity to sustain the operation of equipment before the accurate SOC is accessed, it causes no problem since the model will have chance and time to converge. If not, the safety and functional capabilities of the overall system will be influenced. Failure of a battery might lead to reduced performance, operational damage and even disastrous result. Even if not, minor overcharging or discharging now and then will influence the health of batteries and shorten their lifespan at least.

Traditional UPF methods just use random particles satisfied with distribution like (11) to represent the real capacity of cell. It's no doubt that it will increase the convergence time in a certain degree because of the great amount of particles and big search region, which results from the given random initial SOC in a big solution space and doesn't use the observation information at the very first time.

If it's possible to restrict the given initial value in a less solution space while not bringing great computation complexity, we may access an accurate one with less time. Discrete state space model like (2) is relatively simple and may represent cell behavior to a certain extent. But it's still a complex nonlinear function and not easy to solve. Here we'll employ a linear equation, which is derived from a simplified discrete state space based model with one state, to evaluate its value.

Transforming (2) at the initial sample time with the first-order Taylor series, we get.

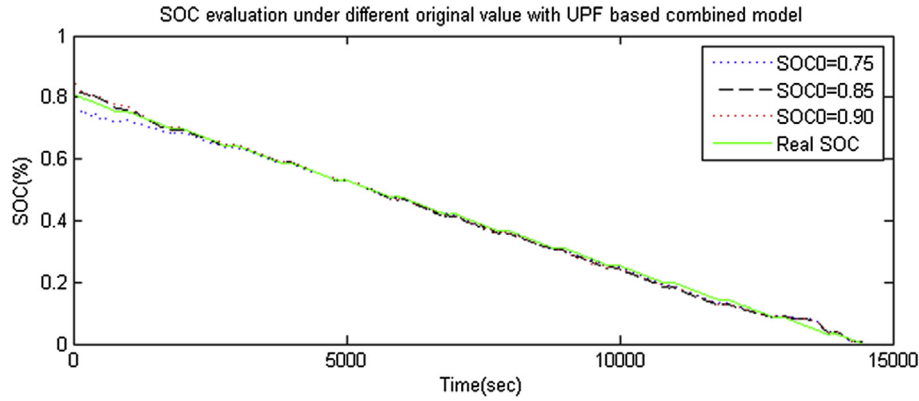


Fig. 4. SOC evaluation under different original value with specified Voc.

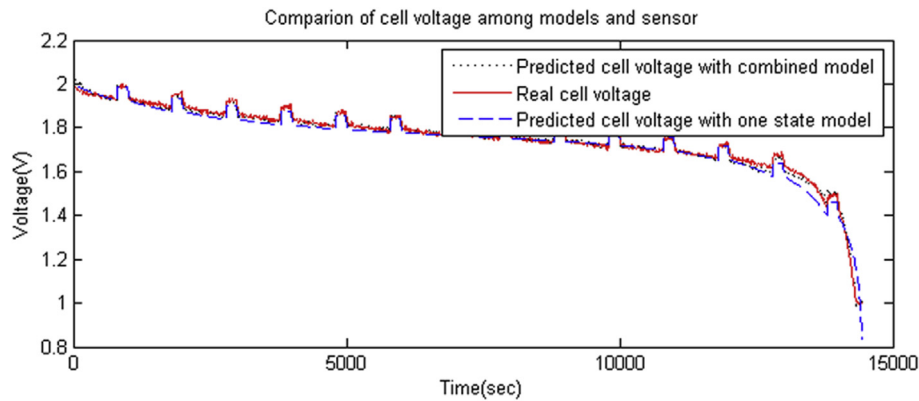


Fig. 5. Comparison of cell terminal voltage among sensor, one state and combined model.

$$y(k) = Cz(k) = [C_1, C_2, C_3, C_4] [1, i(k), 1/SOC(k), SOC(k)]^T \quad (13)$$

where C is the coefficient matrix and $z(k)$ is the parameter matrix at the k th sample time.

Then we get the simplified discrete state space based terminal voltage determination model as follows.

$$Y = ZC \quad (14)$$

where $Y = [y_1, y_2, \dots, y_n]^T$ and $Z = [z_1, z_2, \dots, z_n]^T$. Solving it with a least-square estimation theory, we get the constant coefficient matrix $C = (Z^T Z)^{-1} Z^T Y$. Given the measured parameters like terminal voltage, current and so on, the initial value SOC_0 at the first time is computed as

$$SOC_0 = \frac{y_0 - C_1 - C_2 i - ((y_0 - C_1 - C_2 i)^2 - 4C_3 C_4)^{1/2}}{2C_4} \quad (15)$$

where y_0 is the original terminal voltage. Given an estimated initial value, we may get the solution space of initial capacity $SOC(0)$ as

$$SOC(0) \in (SOC_0 - d_0, SOC_0 + d_0), P\{SOC_0 - d_0 < SOC(0) < SOC_0 + d_0\} = 1 - \gamma \quad (16)$$

where d_0 is the specified search rang at initial time (i.e., $d_0 = 0.1$) and γ is the confidence level derived from training samples. Then model can search cell SOC in a less solution space and the process will be fastened. However, it might fall into a dead zone or local

optimization if real value didn't locate in the given region on some special occasions. Here we employ NLMS (normalized least mean square) method to adapt the search range $d(k+1)$ as

$$d(k+1) = d(k) + \mu \frac{\alpha}{\beta + y(k)^2} e(k) y(k)^*, d(0) = d_0 \quad (17)$$

where μ is the learning rate, α and β is used for influence the stability and convergence speed of model. $e(k)$ is the prediction error between UPF method $y(k)_{upf}$ and real terminal voltage $y(k)^*$. Then model will search cell SOC in a less adaptive solution space

Table 1

Prediction performance comparison among different methods with the combined model.

Prediction performance	Prediction methods		
	EKF	UKF	Improved UPF
Average prediction error	0.0495	0.0361	0.0114
Prediction variance	0.425 e-003	0.270 e-003	0.2593 e-003

Table 2

Prediction speed comparison among different methods with the combined model.

Prediction error	Sample points		
	Prediction methods		
	EKF	UKF	Improved UPF
0.05	43	36	6
0.02	85	76	38

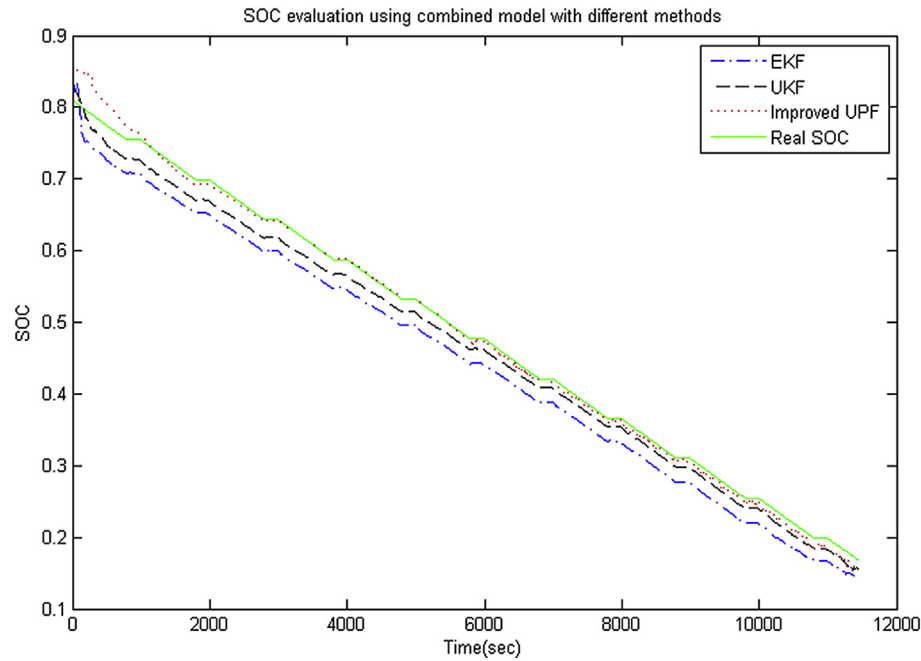


Fig. 6. SOC evaluation using combined model with different methods.

$$SOC(k+1) \in (SOC(k) - d(k+1), SOC(k) + d(k+1)) \quad (18)$$

Assume that particle number is concrete, model would have chance to search optimal results with higher precision while added a little calculation complexity.

The execution diagram of UPF method is shown as Fig. 3 [15,20]. Besides the operation of normal UPF, we use the simplified discrete state space based model with one state to estimate initial cell capacity. Moreover, we employ adaptive filter gain $K(k+1)$ to accelerate the convergence process towards the real state. It's defined as.

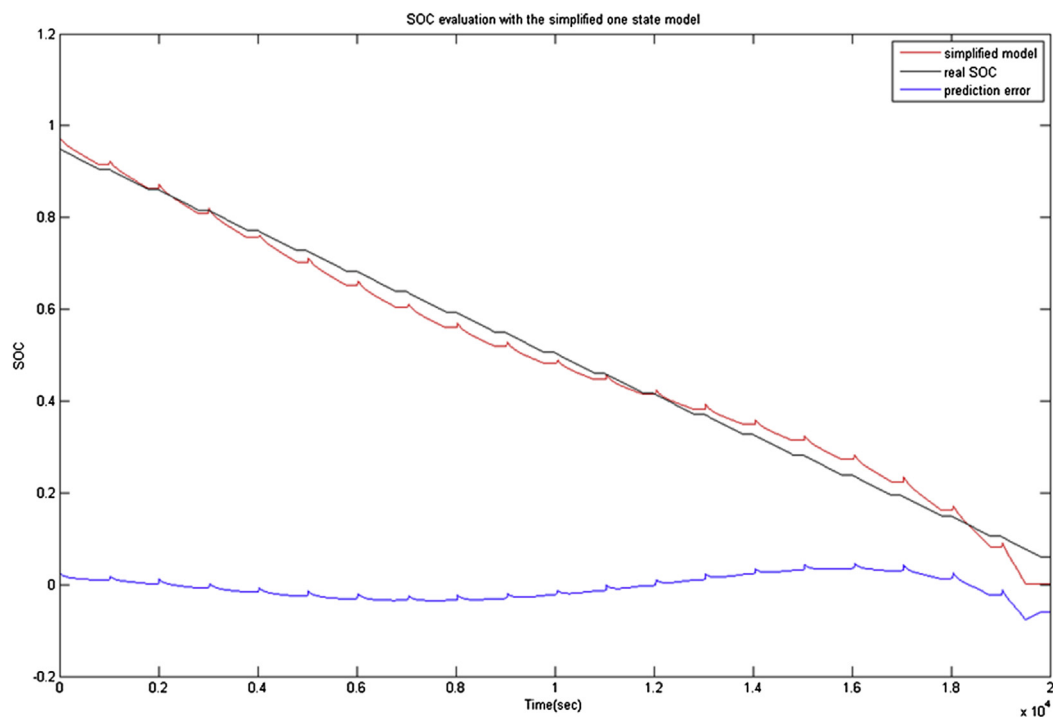


Fig. 7. SOC evaluation with the simplified one state model.

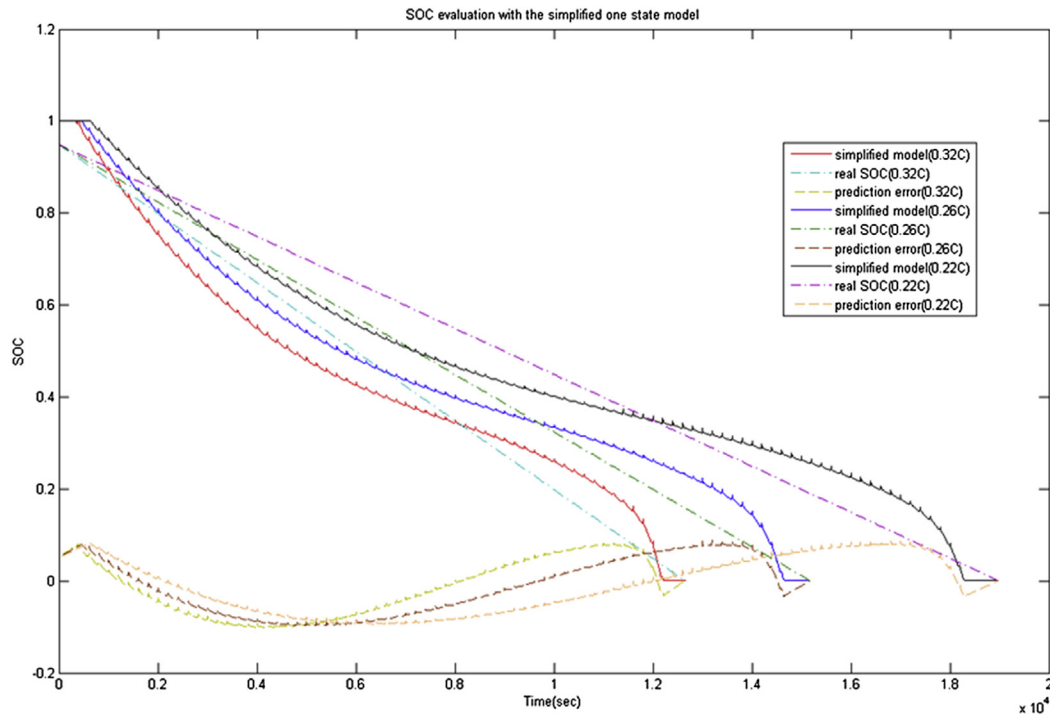


Fig. 8. SOC evaluation with the simplified model under different discharging rate.

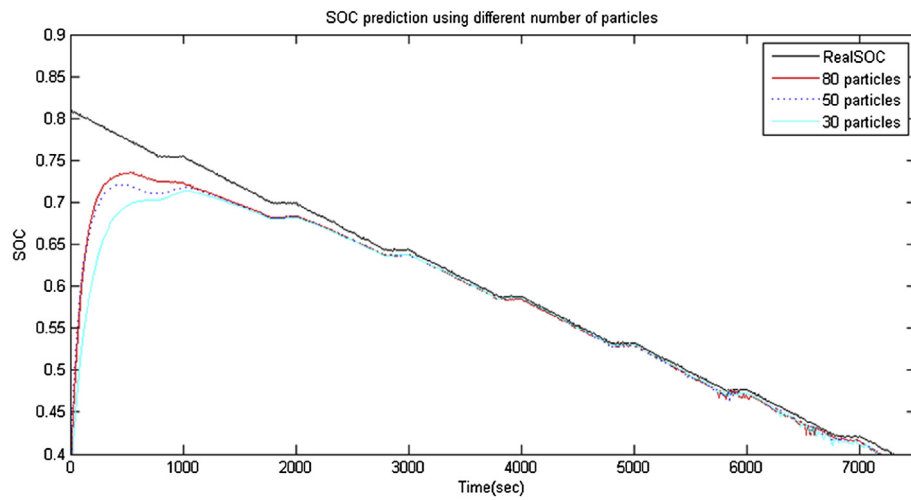


Fig. 9. SOC prediction results using different number of particles when initial value is 0.3.

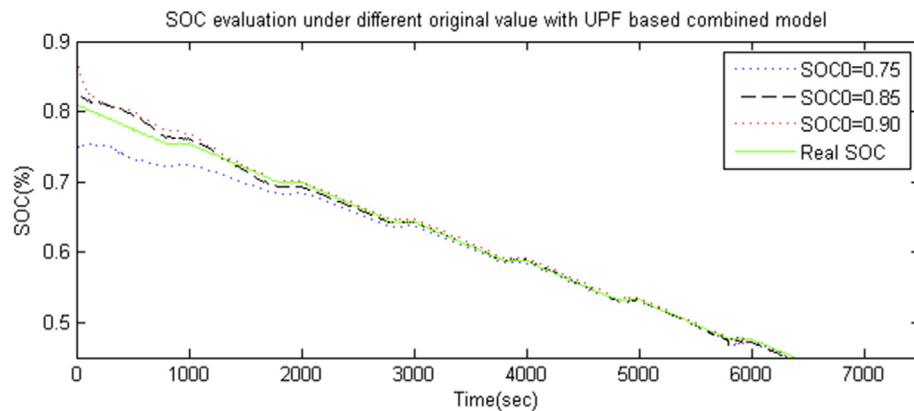


Fig. 10. SOC evaluation under different original value with UPF based combined model.

Table 3

Prediction performance comparison using UPF based combined model with different initial SOC.

Prediction error	Sample points			
	Specified initial SOC			
	0.5	0.75	0.83	0.90
0.05	8	4	3	6
0.02	43	36	32	38

$$\begin{aligned}
 x(k+1)_{ukf} &= x(k)_{ukf} + K(k+1)(y(k+1)^* - y(k+1)_{ukf}) \\
 K(k+1) &= P_{xy}(k+1)P_{yy}(k+1)^{-1} \\
 P_{xy}(k+1) &= \sum W_i(x(k) - x(k)_{ukf})(y(k+1) - y(k+1)_{ukf})^T \\
 P_{yy}(k+1) &= \sum W_i(y(k+1) - y(k+1)_{ukf})(y(k+1) \\
 &\quad - y(k+1)_{ukf})^T + R
 \end{aligned} \quad (19)$$

where $P_{xy}(k+1)$ is the covariance of model state and output and $P_{yy}(k+1)$ is that of model output. They're changed with the weighted output error $(y(k+1) - y(k+1)_{ukf})$ and state evaluation error $(x(k) - x(k)_{ukf})$ of those particles.

6. Results and discussion

To validate the effectiveness of different battery models and the established hybrid UPF based SOC estimation algorithm, experiments and simulations were carried out upon some LEOCH DJ300 (2 V/300 Ah) lead-acid batteries at pulse charging and discharging currents.

As for the equivalent electrical battery model described in (7), results are shown in Fig. 4 when we set three different initial SOC—0.6, 0.81 and 0.9. It shows that the equivalent battery circuit model predicts the trend of SOC rightly. But if given a value far away from the real one, it predicts badly and can't let the predicted value converge to the real one as time goes on. It comes from the shortage of equations to describe the relations between open circuit voltage V_{SOC} and cell SOC.

Fig. 5 presents the evaluation curves of cell terminal voltage with the simple one state model (1,2). Compared to the real value, the output formula behaves well, which mainly comes from its good description of SOC's influence on cell terminal voltage. But there's still a certain difference between the true value and

prediction one, which results from the lack of characterizing the transient response and hysteresis effect of cell. Since that, characterizing the cell open circuit voltage with cell output Equation (3) and employing coulomb efficiency $\eta(i^\pm(k), T(k))$ into model like what has been discussed above, we get the combined state space model for batteries (9). Apply the established model for terminal voltage evaluation of lead-acid batteries, results can be checked in Fig. 5. Contrast to the simple model with one state, the combined cell model has less evaluation error and can simulate battery dynamics like runtime, steady-state and transient voltage responses accurately. Accurate state space model for batteries like the combined one will contribute to the optimal evaluation of available capacity. Introducing the improved UPF algorithm for estimating cell SOC, we get an improved UPF based SOC determination model.

To verify the effectiveness of the combined state space model for batteries, three different methods are applied to evaluate cell SOC, whose performance are shown in Table 1 and 2 and Fig. 6 when set the initial SOC as 0.90. Table 1 gives the detailed prediction performance of SOC among the three different methods: EKF, UKF and improved UPF. Results show that all of them may get a high accuracy with a prediction error less than 5%, which are contributed by the great dynamic behavior description of our established combined SOC determination model. It captures the entire cell dynamic electrical characteristics: open-circuit voltage, available capacity, transient response and hysteresis effect, etc. Among them, the improved UPF method behaves best with a prediction error less than 2%. Table 2 presents the number of required sample points where prediction error starts to enter the specified threshold value like 0.5 and 0.2. Results show that the established model, compared to other methods, converges to the real value more quickly with high accuracy, which can also be found in Fig. 6. It comes mainly from the influence of three aspects. One is the great amount of particles produced from the specified solve vector space, which fasten the search process but also increase a certain calculation complexity. The other is the adaptive filter gain is employed to correct all of the particles according to the prediction error of cell terminal voltage. Another is the good initial SOC accessed from the simplified one state model, whose performance can be found in Fig. 7. To further rectify its availability, experiments are executed under different discharging rates like 0.32C, 0.26C and 0.22C. As depicted in Fig. 8, the prediction value always keeps close to the real one and their prediction error may fall into 10% with the possibility of 97% in our tests. Given a good initial state, the established UPF model would have a chance to search optimal results in a less

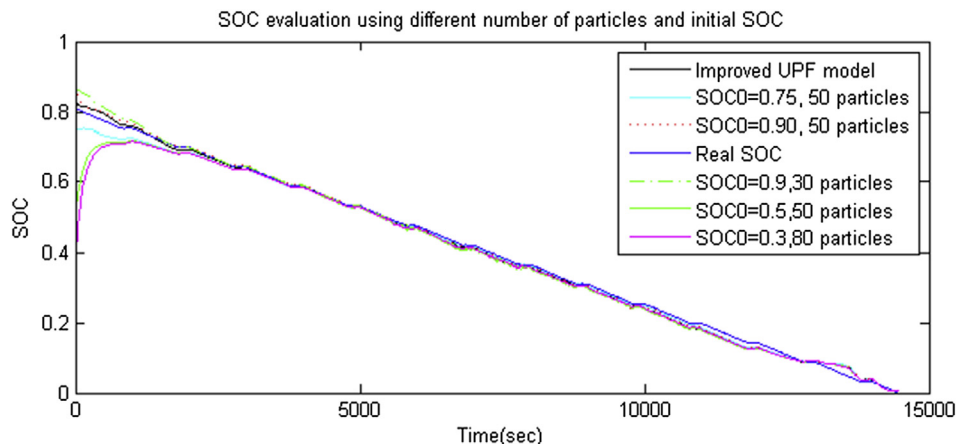


Fig. 11. SOC prediction results using different number of particles and initial available capacity.

solution space at first, which will help to fasten the convergence process.

Since lack of the mean value of SOC, which can't be evaluated like variance after sample training, traditional UPF methods just use a random value to replace it at the initial step. If set a value far away from the real one like 0.3 as the initial available capacity when the real one is 0.81, we may get the performance of combine model with different number of particles as depicted in Fig. 9. It shows that the proposed model has good robustness even given an initial value far away from the real one, which comes from the great description of cell dynamic behavior in our novel combined model and the effective regulation of adaptive filter gain. We may also find that better prediction performance may be accessed to a certain extent when more particles are employed for evaluation, especially at those first steps.

Given different initial SOC like 0.5, 0.75, 0.83 and 0.9, Fig. 10 presents the evaluation results using UPF based SOC determination model with 50 particles. It shows that different initial SOC may influence the time to get an accurate result. Table 3 presents the number of required effective sample points where prediction error starts to enter the specified threshold value when the initial available capacity is 0.81. Results show that it requires less sample points while achieving the same prediction accuracy if given a more accurate initial SOC. Contrast to the normal methods with random initial value, the improved UPF SOC determination model may be 20% faster in general.

To further validate the availability of our established improved UPF based combined model, we employ different number of particles and initial available capacity for test, whose results are presented in Fig. 11. Given an initial value more far away from the real one, more time would be required to converge to the real one with the same number of particles. Although more particles used can help to fasten the convergence speed to a certain extent, greater computation complexity will be produced. Comparatively speaking, the advanced hybrid UPF SOC determination model behaves, whether in convergence speed or accuracy, best even given fewer particles for prediction.

7. Conclusion

This paper brings forward a hybrid UPF based SOC determination model for batteries. The model is mainly composed of two parts. One is the combined state space model for batteries, which takes current as a control input and let SOC and two constructed parameters as state variables to represent cell behavior. It considers the entire dynamic electrical characteristics of batteries: open-circuit voltage, available capacity, hysteresis effect, transient response, temperature, current, etc. The other is the improved UPF based method for cell SOC evaluation, which employs a simplified output equation to get initial available capacity, NLMS method to lessen search region and adaptive filter gain to accelerate the convergence process. Taking lead-acid batteries for example, we apply the established model for test. Numerical simulations show that the evolved combined state space cell model simulates battery dynamics with high accuracy.

The prediction value based on the improved UPF method converges to the real SOC robustly and quickly, and is faster and more accurate than traditional EKF, UKF and UPF approach. Precise and quick knowledge of SOC will allow the controller, without fearing of possible damage caused by deep discharge or overcharge, to confidently use the full operating range of battery pack.

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